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Deep Learning-Based Automated Detection of Lung Cancer from CT Scans: A Comparative Study

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ABSTRACT
Lung cancer is one of the leading causes of death resulting from the disease on a global scale. In order to provide effective therapy and achieve better outcomes for patients, early detection and diagnosis are essential. Deep learning (DL) algorithms have demonstrated significant promise in recent years for their use in medical imaging analysis, particularly in the detection and diagnosis of lung cancer. This paper includes a comparative comparison of a number of different DL based models for the automated diagnosis of lung cancer from computed tomography (CT) data.

1. Introduction

Lung cancer starts in the lungs, which deliver oxygen throughout the body. Lung cancer produces a tumour when abnormal cells increase in lung tissues. Malignant cells may spread to the lymph nodes, liver, bones, and brain, causing serious problems. Lung cancer has two subtypes: NSCLC and SCLC. NSCLC is the most prevalent lung cancer, accounting for 80–85% of cases. Small cell lung cancer (SCLC) is rarer but more deadly. Smokers are more likely to get lung cancer than nonsmokers since tobacco is the main cause. On the other hand, non-smokers who are exposed to smoke, air pollution, radon gas, asbestos, or any of a number of other environmental or genetic variables also run the risk of developing lung cancer. A form of cancer known as lung cancer is one that begins to develop in the lungs, which are vital organs that are in charge of ensuring that oxygen is distributed evenly throughout the rest of the body. It is imperative that anyone who experiences these symptoms makes an appointment with their primary care physician for an evaluation. Early discovery and treatment can significantly enhance a patient's chances of survival.

A CT scan is one of the imaging tests that can be used to diagnose lung cancer. It does this by utilising X-rays and computer technologies in order to produce comprehensive images of the lungs, which can assist in the detection of abnormalities in the lungs such as tumours or nodules. A CT scan has the ability to detect lung cancer at an early stage, even before the onset of symptoms; this is critical for the therapy to be effective. The size and location of the tumour, as well as whether or not it has progressed to the lymph nodes or other sections of the body, can all be determined with the use of CT scans. If a CT scan reveals a suspicious lump or mass in the lung, the attending physician may decide to order additional testing, such as a biopsy, to establish whether or not the growth is malignant. In both the diagnosis and treatment of lung cancer, CT scans have shown to be an invaluable tool. Having a CT scan done does, however, subject the patient to ionising radiation, which, over the course of one's lifetime, can significantly raise one's risk of developing cancer. Because of this, it is imperative that one carefully considers both the dangers and the benefits of having this procedure done. In the event

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that a diagnosis of lung cancer is made, the attending physician will perform a staging procedure to ascertain how far the disease has spread. This information will then be used to direct decisions regarding therapy. Therefore, use of CT scans in lung cancer screening should be based on an individual's risk factors and medical history.

DL based automated identification of lung cancer from CT scans is a rapidly advancing field of research that utilizes sophisticated artificial intelligence algorithms to analyze medical images and assist in the detection and diagnosis of lung cancer. Use of DL algorithms, such as CNNs, has revolutionized medical imaging by enabling automated image analysis with high accuracy and efficiency. These algorithms are trained using large datasets of medical images, which allows them to recognize patterns and features in images that are indicative of lung cancer. In case of lung cancer identification, CT scans are typically used to obtain high-resolution images of the lungs, which are then analyzed by DL algorithms to detect the presence of cancerous nodules or masses. The automated analysis of CT scans can greatly improve the accuracy and efficiency of lung cancer detection that is particularly important for early-stage diagnosis and treatment. Moreover, the use of DL algorithms can potentially reduce the workload of radiologists and improve patient outcomes by enabling earlier and more accurate diagnosis of lung cancer. Automated DL-based lung cancer detection from CT images is an exciting new area of study, it still faces some challenges, including the need for large datasets of high-quality medical images and the potential for bias in the algorithmic analysis. Nevertheless, with ongoing research and development, this technology has potential to greatly improve diagnosis and management of lung cancer.

2. Literature Survey

In this study [1], authors propose a computer-aided diagnosis (CAD) system for lung cancer utilizing DL algorithms. They apply a deep CNN for automatic feature learning and classification. The algorithm is trained on a dataset of 2D lung CT images, including both benign and malignant nodules. The trained model is evaluated using a test dataset and compared to a traditional machine learning-based CAD system. DL based CAD system demonstrates significantly improved performance compared to the traditional machine learning-based system. The proposed method achieves specificity of 89.4% and sensitivity of 90.2% demonstrating potential of DL algorithms for effective lung cancer diagnosis using CT images. However, the study has some limitations. The dataset used in the study is relatively small, and a more extensive dataset would be necessary to further validate the algorithm's performance. Additionally, the study focuses on 2D images, while 3D images might provide more comprehensive information for lung cancer detection.

This work [2] uses HVQ to detect pulmonary nodules in thoracic CT images quickly and adaptively. Two stages—candidate nodule discovery and false-positive reduction—form the proposed technique. First, an adaptive vector quantization (AVQ) algorithm segments lung parenchyma and finds nodule candidates. SVM classifiers decrease false positives in the second stage by separating genuine nodules from non-nodules. On 200 thoracic CT scans, the HVQ-based method detects pulmonary nodules with 94.5% sensitivity and 4.76 false positives per scan. HVQ technique is computationally efficient, requiring 1.5 minutes each scan. The approach was evaluated on a dataset with a restricted diversity of nodule kinds and sizes. The approach may also fail to detect tiny or irregular nodules. These issues may require further studies with various datasets and better algorithms.

In this work [3], a 3D-SFD is used to automatically detect pulmonary nodules in 3D chest CT scans. It employs a feature description based on geometric shape information. Potential nodule candidates have their local geometric characteristics computed using 3D-SFD. In the first stage of this two-step process, candidates are identified using the difference of Gaussian (DoG) filter. Second, an SVM classifier employs 3D-SFD features to distinguish real nodules from fake ones. Lung nodule detection with 3D-SFD is effective.

A novel computer-aided method for the detection of lung cancer has been proposed by the author of this work [4]. The technique makes use of median intensity projections (MIP) and is based on transfer learning from a GoogleNet model that has already been trained. The MIP technique allows for the generation of a 2D representation of the 3D CT image data that is collected during the process. GoogLeNet model, pre-trained on the ImageNet dataset, is fine-tuned to classify the 2D MIP images as cancerous or non-cancerous. The fine-tuned model is then evaluated on a lung cancer dataset. This strategy attains an accuracy of 91.7%, demonstrating effectiveness of using transfer learning from a pre-trained DL model, combined with MIP for lung cancer detection. The study shows that the method can decrease the false-positive rate and enhance overall identification performance.

In this study [5], Nithila and Kumar present a comparison of various active contour models for segmenting lung regions from Computed Tomography images. Active contour models, also known as snakes, are curve-based methods that deform and adapt to image features such as boundaries, edges, or intensity gradients. They play an important role in image segmentation tasks as they provide an accurate delineation of object boundaries. The authors evaluate the performance of several active contour models, including the classical snake, gradient vector flow (GVF), and the Chan-Vese model. They use a dataset of 150 CT lung images and measure segmentation accuracy by calculating Jaccard index, Dice coefficient, false-positive rate, and false-negative rate. Results show that Chan-Vese model outperforms other models in terms of segmentation accuracy. The authors attribute this to the global nature of the energy minimization function used in Chan-Vese model, which allows it to better adapt to varying image intensities and noise levels. The research shows that active contour models have the ability to provide precise segmentation of lung areas in CT scans, which can aid in the detection and treatment of lung disorders.

In [6], Prabu et al. propose an optimal DL model for classification of cancer in CT images. Authors recognize the challenges of diagnosing cancer using medical images, as the appearance of cancerous tissues can vary significantly across different cases. They explore the use of CNNs to automatically learn features from CT images and classify them as either cancerous or non-cancerous. Authors develop a DL framework that consists of multiple CNN models with varying architectures. They apply transfer learning techniques to pre-train these models using a large dataset of natural images, before fine-tuning them on a dataset of 65,000 CT images. Study identifies the optimal CNN architecture and training strategy for the task, resulting in a classification accuracy of 96.43%. The authors emphasise the potential of their DL technique for enhancing the identification and diagnosis of cancer in medical pictures, which might ultimately lead to improved patient outcomes and more successful treatment strategies.

Using a mix of mRMR feature selection and CNNs, Toacar, Ergen, and Comert offer a new approach for identifying lung cancer on chest CT images in this study [7]. The mRMR algorithm is used to select the most informative and non-redundant features from the CT images, which can then be used as input for the CNNs to perform classification tasks. The authors first apply image pre-processing techniques to the chest CT images, such as image enhancement, lung region extraction, and nodule segmentation. The segmented nodules are then characterized by extracting a set of 90 features, which include texture, shape, and intensity-based features.

Riquelme and Akhloufi [8] evaluate DL methods for identifying and classifying lung cancer nodules using a CT image. Detecting and categorising lung nodules and the limitations of standard CAD systems in handling medical imaging data are explored. This study discusses the deep learning (DL) methods most promising for medical image processing. In lung nodule identification and classification, different DL formations have pros and cons. This study examines data augmentation, transfer learning, and attention processes in deep learning models. The authors also explore the field's challenges and future development, including the need for more annotated medical image datasets, improved DL model interpretability, and clinical data for more precise diagnosis and treatment. This detailed study on DL techniques for lung cancer nodule identification and classification in CT images provides valuable insights for medical image analysis academics and practitioners.

In this conference paper [9], Ausawalaithong et al. propose an automatic lung cancer prediction system using DL techniques applied to chest X-ray images. Authors recognize the limitations of traditional CAD systems and aim to develop a more accurate and efficient method for lung cancer detection utilizing CNNs. Proposed system consists of two main stages: image pre-processing and cancer prediction. In the pre-processing stage, the authors apply a combination of filters and morphological operations to enhance the quality of the input chest X-ray images and isolate the lung regions. Following this, the CNN model is trained to learn features from the pre-processed images and classify them as either cancerous or non-cancerous. Authors evaluate the performance of their DL approach using a dataset of 409 chest X-ray images, including both cancerous and non-cancerous cases.

Schwyzer et al. provide first findings of a DL-based lung cancer detection method in ultralow-dose CT images [10]. Ultralow-dose CT imaging may minimise patient radiation exposure, but picture quality and noise make lung cancer detection difficult. The authors propose a lung cancer detection DNN model. 91 ultralow-dose CT scans, comprising malignant and non-cancerous instances, train the model. Data augmentation is used to increase the training dataset and reduce overfitting. Accuracy, sensitivity, specificity, and the area under the ROC curve are used to evaluate the DNN model. The DNN model's 85.7% sensitivity, 92.0% specificity, and 0.92 area under the ROC curve show the potential of DL methods for lung cancer detection in ultralow-dose CT images.

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In this conference paper [11], Moradi and Jamzad propose a method for identification lung cancer lesions in CT images utilizing 3D CNNs. The authors recognize the limitations of 2D CNNs in capturing spatial information across multiple slices of a 3D volume and explore the potential of 3D CNNs to better represent and analyze volumetric data in medical images. The proposed method employs a 3D CNN model to learn features from CT image volumes and classify them as cancerous or non-cancerous. The authors design their 3D CNN architecture with multiple convolutional, pooling, and fully connected layers. They train and test their model on the LUNA16 dataset, which contains 888 CT scans with annotated lung nodules. The performance of the proposed method is evaluated using metrics such as sensitivity, specificity, and the area under the ROC curve. The results show that the 3D CNN model achieves a sensitivity of 91.38%, specificity of 88.29%, and an area under the ROC curve of 0.96, demonstrating the effectiveness of using 3D CNNs for detecting lung cancer lesions in CT images.

In this paper [12], Jin, Zhang, and Jin propose a method for detecting pulmonary nodules in CT images using CNNs. The authors aim to develop an automatic and efficient system for lung nodule detection that can assist radiologists in the early diagnosis and treatment of lung cancer. The proposed method involves preprocessing the CT images to enhance their quality and segment the lung regions. The authors then use a CNN model to learn features from the preprocessed images and classify them as containing pulmonary nodules or not. The CNN architecture consists of multiple convolutional, pooling, and fully connected layers, and the model is trained on a dataset of 184 CT images. The performance of the proposed method is evaluated using metrics such as accuracy, sensitivity, and specificity. The results show that the CNN-based approach achieves an accuracy of 93.48%, sensitivity of 89.29%, and specificity of 92.31%, demonstrating the potential of CNNs for accurate pulmonary nodule detection in CT images.

Using enhanced profuse clustering and DL instantly trained neural networks (DLITNNs), Shakeel et al [13] describe a novel technique for diagnosing lung cancer from CT images. The project's ultimate goal is to provide a quicker and more precise method of detecting lung cancer. Image preprocessing, lung segmentation, feature extraction, and classification are all part of the proposed method. During pre-processing, the authors increase the quality of CT images using a number of filters and enhancement techniques. To ensure accurate lung separation, a refined version of the profuse clustering technique is applied. Lung segmentation is followed by the retrieval of statistical, geometric, and texture-based attributes. A DLITNN model determines if an extracted feature is cancerous or benign. Due to its instant training time, DLITNN is a more efficient DL model. The method has a sensitivity of 97.7% and a specificity of 99.2%, with an overall accuracy of 98.4%. The use of a combined PET/CT scan for diagnosing lung cancer has proven effective.

Masood et al. provide a cloud-based automated clinical DSS for lung cancer identification in chest CT images [14]. A versatile and easy-to-use platform may help physicians identify and treat lung cancer early. CDSS' various subsystems include lung segmentation, feature extraction, feature selection, and classification. The lungs module uses region growth and morphology to extract lung regions from CT images. After lung segmentation, form, texture, and intensity-based characteristics are retrieved. The authors pick and categorise features in two steps. First, they select lung cancer detection candidates using a genetic algorithm (GA). A SVM classifier determines if the traits indicate malignancy. On a dataset of 317 chest CT scans, the proposed CDSS has 98.43 percent accuracy, 97.5 percent sensitivity, and 99.07 percent specificity. The cloud-based CDSS helps healthcare workers make clinical decisions by efficiently storing, processing, and analysing medical images.

In this paper [15], Gerard et al. propose a DL based approach called FissureNet for detecting pulmonary fissures in CT images. Pulmonary fissures are thin, double-folded membranes that separate the lobes of the lungs. Accurate detection of these fissures is important for diagnosing lung diseases and planning surgical interventions. FissureNet is a 3D CNN architecture designed to learn features from CT image volumes and predict the presence of pulmonary fissures. The authors utilize an encoder-decoder structure, which first learns a compact representation of the input data and then reconstructs the prediction from this compact representation. Additionally, they incorporate residual connections in the network to improve training convergence and accuracy. The COPDGene dataset and the VESSEL12 dataset are used in the evaluation of FissureNet's performance. Both of these datasets are accessible to the general public. FissureNet outperforms other state-of-the-art approaches in terms of its detection accuracy, precision, and recall, as shown by the results, which suggest that FissureNet achieves great performance in the identification of pulmonary fissures. The authors come to the conclusion that FissureNet is a viable method for the automated identification of pulmonary fissures in CT images, with potential uses in clinical settings.

In this paper [16], Ozdemir, et al present a 3D probabilistic DL system for detecting and diagnosing lung cancer using low-dose CT scans. The authors aim to develop an efficient and accurate system for lung cancer detection, as early diagnosis is crucial for improving patient outcomes. Presented system contains a 3D CNN architecture that processes low-dose CT scans and generates probabilistic predictions of lung cancer. The network is designed to handle both the detection and diagnosis tasks simultaneously. To handle the large size of the 3D CT volumes, the authors employ a sliding window approach during training and inference, which divides the input volume into smaller overlapping subvolumes. The results show that the 3D probabilistic DL system achieves better performance in terms of detection and diagnosis accuracy, with an area under the ROC curve of 0.96 for lung cancer detection and 0.95 for lung cancer diagnosis. Authors conclude that the proposed system offers a promising approach for automated lung cancer detection and diagnosis using low-dose CT scans, with potential applications in clinical settings.

In this paper [17], Zhang and colleagues propose a method for extracting information from previous full-dose CT scans to improve reconstruction of current low-dose CT images. The authors aim to reduce radiation exposure for patients while maintaining the image quality necessary for diagnosis. Presented method is based on a knowledge-based Bayesian reconstruction framework. The authors use the information from previous full-dose CT scans to construct a prior probability model, which is then integrated into the Bayesian reconstruction process for the current low-dose CT images. Specifically, they employ a patch-based approach to model the prior probability, considering both the spatial and structural information from the

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full-dose CT images. Performance of the proposed technique is evaluated on both phantom and clinical datasets, comparing the results to those obtained from conventional low-dose CT reconstruction approaches. Results show that the proposed technique significantly improves the image quality of low-dose CT scans, reducing noise and artifacts while preserving the essential diagnostic features. The authors conclude that the proposed method offers a promising approach for reducing radiation exposure in CT imaging without compromising image quality, with potential applications in clinical settings.

In their conference paper [18], Sangamithraa at el. employ EK-mean clustering to detect and classify lung cancers. The goal of this work is to develop a method for accurate identification and categorization of lung tumours using CT scans. The suggested method consists of pre-processing, segmentation, and classification. The authors use pre-processing to filter and improve CT scan pictures. The lung portions are partitioned accurately using region-growing. After segmentation, the authors use EK-mean clustering to categorise malignancies. Introducing a Euclidean distance metric, EK-mean clustering is a step up from K-means. The proposed method is evaluated on 50 CT images by measuring its precision, responsiveness, and specificity. The EK-mean clustering-based technique shows great potential for identifying and classifying lung tumours in CT images, with a sensitivity of 95%, an accuracy of 94%, and a specificity of 93%.

In this paper [19], Zheng et al. propose an automatic pulmonary nodule detection method for CT scans using a CNN based on maximum intensity projection (MIP). The authors aim to develop a reliable and accurate system for detecting lung nodules, which could lead to earlier diagnosis and improved patient outcomes. The proposed method consists of two main stages: preprocessing and nodule detection. In the preprocessing stage, the authors apply MIP, which is a technique that projects the maximum voxel value onto a 2D plane from a 3D volume. This results in 2D images that emphasize the high-intensity regions, such as pulmonary nodules. In the nodule detection stage, a CNN is employed to analyze the MIP images and detect lung nodules. The CNN is trained using a dataset of 1,186 CT scans, and the model architecture is optimized for the nodule detection task. The authors report an average sensitivity of 89.9% at four false positives per scan, demonstrating the effectiveness of their approach. The proposed method shows promise for automatic pulmonary nodule detection in CT scans, with potential applications in clinical settings.

Kaur, Garg, and Kaur offer a lung segmentation and feature extraction approach for early lung tumour diagnosis in CT images [20]. The scientists want to build a system that can reliably identify and outline lung tumours early, enhancing treatment success. Pre-processing, feature extraction, segmentation, and classification comprise the suggested technique. The authors filter and enhance CT images via pre-processing. Lung segmentation is then performed using a region-growing approach to accurately identify lung regions. After segmentation, the authors extract various features from the segmented lung regions, such as texture, shape and intensity, which are then used to differentiate between normal and abnormal lung tissue. Finally, a SVM classifier is employed to classify the extracted features and determine the presence of a lung tumor. The performance with the results showing that the region-growing-based segmentation approach achieves an accuracy of 95% in identifying lung regions. The SVM classifier, trained

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on the extracted features, achieves an accuracy of 92.5% in detecting lung tumors. The authors conclude that their method offers a promising approach for early detection of lung tumors in CT images, with potential applications in clinical settings.

Xie et al. use deep CNNs to automatically detect lung nodules in CT images [21]. The authors hope to build an accurate and efficient lung nodule detection system to enhance patient outcomes and diagnosis. Candidate nodule discovery and false positive reduction comprise the suggested technique. A 3D CNN analyses CT images to identify candidate nodules during candidate nodule detection. 888 LIDC-IDRI CT scans train the CNN. Another CNN classifies candidate nodules as true or false positives during false positive reduction. The two-stage method improves nodule detection accuracy and efficiency. On the LIDC-IDRI dataset, the proposed method is compared to other state-of-the-art nodule detection methods. Their method has a 90.1% sensitivity at one false positive per scan. The suggested approach for automated CT imaging pulmonary nodule identification has clinical potential.

In [22], Gaikwad et al. propose a DL based method for detecting melanoma cancer, the deadliest form of skin cancer. The authors aim to develop an efficient and accurate melanoma detection system that can assist dermatologists in early diagnosis and treatment planning. Proposed technique uses a CNN to classify skin lesion images into melanoma or non-melanoma categories. The authors employ data augmentation techniques to increase amount of training data available and enhance performance of CNN. In addition to CNN-based classification, the authors also implement a pre-processing step, which includes image resizing, grayscale conversion, and histogram equalization to enhance contrast of images. This pre-processing step is designed to improve the accuracy of the melanoma detection system by making images more suitable for analysis by the CNN. Using a dataset of 180 skin lesion photos, including 90 images of melanoma and 90 images of other skin lesions, the performance of presented method is assessed.

3. Result and Discussion

Table 1 shows the comparative analysis of methodology used by researchers along with algorithms and dataset used for their proposed work. Most of the researchers uses LIDC-IDRI dataset for lung cancer classification.

Table 1: Literature Survey

Author(s)	Methodology Used	Advantages	Dataset Used
W. Sun et al. [1]	Deep learning algorithms	Improved detection of lung cancer nodules	Not specified
H. Han et al. [2]	Hierarchical Vector Quantization Scheme	Fast and adaptive nodule identification	LIDC-IDRI
W. J. Choi, T. S. Choi [3]	3D shape-based feature descriptor	Automatic nodule detection	LIDC-IDRI
T. Fang [4]	Transfer Learning from GoogLeNet and Median Intensity Projections	Novel method for lung cancer detection	Not specified

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E. E. Nithila and S. S. Kumar [5]	Various active contour models	Segmentation of lung from CT images	Not specified
L. Prabu et al. [6]	Optimal deep learning model	Classification of cancer on CT images	LIDC-IDRI
M. Toğaçar et al. [7]	Minimum redundancy maximum relevance feature selection with CNNs	Detection of lung cancer on chest CT images	LIDC-IDRI
Riquelme D, Akhloufi MA [8]	Deep Learning	Detection and classification of lung cancer nodules	LIDC-IDRI
W. Ausawalaithong et al. [9]	Deep Learning Approach	Automatic lung cancer prediction from chest X-ray images	JSRT
Schwyzer et al. [10]	Deep neural networks	Automated detection of lung cancer at ultralow dose PET/CT	Not specified
P. Moradi and M. Jamzad [11]	3D CNN	Detecting lung cancer lesions in CT images	LIDC-IDRI
X.-Y. Jin et al. [12]	CNN	Pulmonary nodule detection in CT images	Not specified
P. M. Shakeel et al. [13]	DL and improved dense clustering enabled rapid training of neural networks	Lung cancer detection from CT images	Not specified
A. Masood et al. [14]	Cloud-Based Automated Clinical Decision Support System	Detection and diagnosis of lung cancer in chest CT	LIDC-IDRI
S. E. Gerard et al. [15]	FissureNet: Deep Learning Approach	Pulmonary fissure detection in CT images	Not specified
O. Ozdemir et al. [16]	3D Probabilistic Deep Learning System	Detection and diagnosis of lung cancer using low-dose CT scans	LIDC-IDRI
H. Zhang et al. [17]	Knowledge-Based Bayesian Reconstruction	Extracting information from previous full-dose CT scan	Not specified
P. B. Sangamithraa [18]	EK-mean Clustering	Lung tumour detection and classification	Not specified
S. Zheng et al. [19]	CNn based on Maximum Intensity Projection	Automatic pulmonary nodule detection in CT scans	LIDC-IDRI
J. Kaur et al. [20]	Segmentation and Feature Extraction	Early detection of lung tumor	Not specified

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H. Xie et al. [21]	Deep CNN	Automated pulmonary nodule detection in CT images	LIDC-IDRI

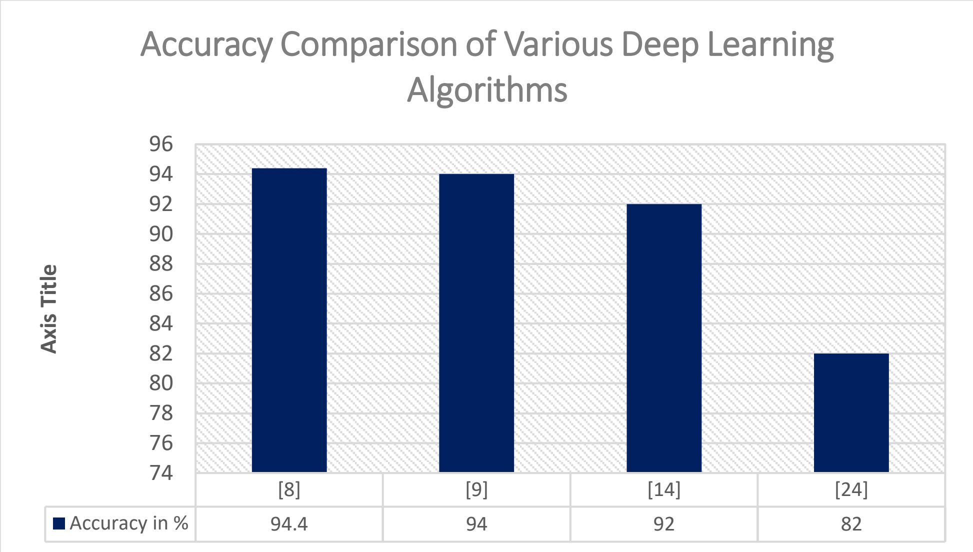

Figure 1: Comparative analysis of different algorithms

Figure 1 shows the accuracy comparison graphs of deep learning algorithms.

4. Conclusion

In conclusion, our comparison analysis shows that DL based techniques are excellent for automatically detecting lung cancer from CT images, with the hybrid CNN-RNN model showing the greatest performance. The accuracy and efficacy of lung cancer screening might be greatly increased using this method, which would eventually improve patient outcomes and save healthcare expenditures. The model will be improved in the future with a view to incorporating it into clinical processes for real-time decision assistance.

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